New Methods for Stress Assessment and Monitoring at the Workplace

Davide Carneiro, Paulo Novais, Juan Carlos Augusto, and Nicola Payne

Abstract—The topic of stress is nowadays a very important one, not only in research but on social life in general. People are increasingly aware of this problem and its consequences at several levels: health, social life, work, quality of life, etc. This resulted in a significant increase in the search for devices and applications to measure and manage stress in real-time. Recent technological and scientific evolution fosters this interest with the development of new methods and approaches. In this paper we survey these new methods for stress assessment, focusing especially on those that are suited for the workplace: one of today's major sources of stress. We contrast them with more traditional methods and compare them between themselves, evaluating nine characteristics. Given the diversity of methods that exist nowadays, this work facilitates the stakeholders' decision towards which one to use, based on how much their organization values aspects such as privacy, accuracy, cost-effectiveness or intrusiveness.

Index Terms—Stress, Human-Computer Interaction, Survey, Ambient Intelligence.

1 Introduction

The topic of stress currently attracts significant attention, not only in research but on social life in general. The public is aware of this phenomena and of its consequences at many levels (e.g. psychological, physical, social, well-being). On the other hand, researchers in many different fields work to find new ways to assess, monitor and reduce stress, that can not only answer the interest of the public but also allow a better understanding of the phenomenon.

Of all the important perspectives on stress, a particularly interesting one concerns occupational stress. While occupational stress affects individuals at a personal level, there is a special interest in the effects at the organizational level, mainly its economic impact. There is a broad consensus that job stress has a significant economic impact, amounting to billions of dollars each year in the United States alone [1]. These losses are due to the increased cost of medical insurance, excess of pressure on medical facilities and professionals, lower productivity, human error, absenteeism, and so forth [2].

This calls for the development and implementation of initiatives for stress management that can not only reduce these costs but, at the same time, improve well-being, workplace quality, among other indicators.

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The main aim of this paper is thus to survey existing methods for stress assessment and monitoring in Humans. Specifically, we focus on methods that can be used continuously throughout the day in milieus such as the workplace. We seek ways to measure stress over long periods of time, that do not influence the workers' routines [3].

Although we address methods that can be deemed as more traditional (e.g. physiological sensors, questionnaires) in the sense that they have been in use for decades, we focus especially on novel methods that, for their characteristics, raise significant interest. Moreover, given their novelty, these methods pose new challenges at several levels (e.g. technological, ethical [4]) and caution is advised when using them.

Specifically, we focus on methods that can be used in line with Ambient Intelligence systems, allowing a continuous monitoring of the users while they perform their daily activities, without interference [5]. In this sense, it is important to start by clarifying two concepts that are often found in research in this field that, although different, are frequently used interchangeably: *invasive* and *intrusive*. In a physiological sense, an action is called invasive if it infiltrates, cuts or destroys healthy tissue, namely the skin. An intrusive action, on the other hand, is one that intrudes or interferes in one's space, resulting in (often unwanted) changes in routines.

Consequently, a non-invasive approach is one in which there is no invasion of the user's body. This includes most of the sensors currently used for stress monitoring (e.g. skin temperature, heart rate). A non-intrusive approach, on the other hand, must meet more strict criteria. Specifically, it cannot change, in any way, the routine of the user. This means that users must be able to carry out their daily activities as if they were not being monitored. This includes, by definition, approaches based on computer vision or speech analysis, for example. Nonetheless, other types of intrusion may be present, as will be addressed later (e.g. the use of a video camera may be seen as a privacy intrusion). These approaches will thus be compared, namely in terms of their degree of intrusion, so that researchers or practitioners can decide on the best to use for each domain of application.

The paper is organized as follows. Section 2 addresses the fields of Ambient Intelligence and Ambient Assisted Living, describing their main characteristics and aims. Section 3 describes stress, its origin, its effects at several levels and its importance, especially in the workplace. Section 4 addresses traditional approaches for stress assessment, namely those based on physiological sensors and questionnaires. Section 5 contains the core of the paper, detailing several new methods for stress assessment that present significant advantages when compared to more traditional ones, making them more suitable to be used in the workplace. These methods are critically analyzed and compared in Section 6, allowing practitioners to decide on the best method to use in each specific domain. Finally, Section 7 presents a discussion of the main conclusions of this work and points out future research trends and directions.

2 Ambient Intelligence and Ambient Assisted Living

Computer Science has been fast evolving in the last few decades pushed by technological advances. Innovation in electronics had created the need for the field of computing in general to get more involved with decentralized computation. Nowadays it is possible to embed reasonably useful computational capabilities in a small space and at an affordable cost.

Mobile phones, tablets, PCs, smart watches which can track several health parameters, smart toys with ingenious independent behaviour, houses which can control comfort and safety aspects of our life, smart classrooms, smart offices, automated farming, autonomous cars, autonomous airplanes, and a myriad of other advances have brought computing very close to our daily lives in a way most did not anticipated just a couple of decades ago and it was the topic of science fiction films. This transformation was not simultaneous: the most influential work in this direction is acknowledged to have started within the areas of “Ubiquitous Computing” and “Pervasive computing” [6]. It then progressed into other concepts with “Ambient Intelligence” [7] and “Intelligent Environments” [8].

All these can be described as attempts to create “...digital environments that proactively, but sensibly, support people in their daily lives.” [9]. Some of these areas put more emphasis in different aspects of the system as developers were gaining experience and understanding of the most challenging aspects of these multi-disciplinary systems which brought together sensing, networking, human-computer interaction, artificial intelligence, and software engineering, to mention some of the most relevant disciplines.

Key to the success of all these systems is that to please the intended users, the system has to have an understanding of the context where services have to be delivered. The subtler this understanding is, the more informed the system to satisfy a given user. This includes understanding personal things, like the preferences or the emotional state of a user. Say I like to be greeted with some ambient music when I arrive home. The system needs to know that I prefer music from J.S. Bach to music from Iron Maiden, but not any music from J.S. Bach will do every day, so if some days I am in need of more cheerful music then perhaps a cantata may be a good choice and if one day I am in need of more relaxing music I may prefer some pieces from the Well-Tempered Clavier. Some days I may not want any music at all. How is the system going to know that? See section on “Mindreading” in [8].

The example above may not seem too important as it is related to leisure. However, one of the most important possible applications and one of the most widely researched and tried benefit expected from this area is what is often referred to as Ambient Assisted Living (AAL). “AAL refers to intelligent systems of assistance for a better, healthier and safer life in the preferred living environment and covers concepts, products and services that interlink and improve new technologies and the social environment.” [10]. There are several definitions of AAL. However, most of them put emphasis on the safety, health, and well-being of individuals. Although these type of benefits are usually placed in the home environment, AAL system do not have to be restricted to houses and can actually be delivered in other places such as the work place, where many people spend a considerable part of their lives. AAL services are also most often associated with older people and in particular with senior citizens experiencing some category of dementia. Although it is true those are the type of applications which have most funding so far, hence more interest, it is clear AAL can help citizens with other conditions, Parkinson’s disease, Down’s syndrome, autism, etc. From this we can also state that AAL benefits are not only for senior citizens but it is a type of service with the capacity to improve the quality of life of all citizens.

Having introduced AAL as a kind of specific branch of Ambient Intelligence with specific interest in the welfare of citizens, it is clear that a system given such a responsibility has to have substantial capabilities to understand what a person is going through at a given time as well as powerful decision-making. For a system to be capable of looking after the welfare of an individual, it has to understand that individual deeply. It is not only a matter of knowing about the preferences of that individual and how those preferences are linked to different situations but it also implies being capable to understand how a user feels ‘now’. We can revisit the ambient music scenario, but now imagine the person in question is depressed. If the ambient music is the wrong one for the mood of the user, it may have a detrimental effect, increasing the levels of anxiety, depression or stress of the individual in question. Stress may lead to wrong decisions, which in turn can have undesired consequences resulting in more stress [11].

If understanding a specific mental state of an individual like feeling stressed is so important for the success of AAL, how can we do it? There are different approaches, some of them more behavioural and others more biological. By these we mean that some answers to the challenge try to understand how the individual is behaving, e.g., body language, whilst the latter approach relies more on measuring specific personal body parameters which can provide an indicator, e.g. high blood pressure as a potential indicator of stress. The next sections of this paper provide a more specific account of these approaches and highlight the challenges behind each of these options.

3 Stress as a Broad Cognitive Process

Stress and related concepts can be traced as far back as written science and medicine [12]. Likewise, its influence at both an organizational and individual level is nowadays unquestionable [13].

3.1 Fundamental Concepts

In modern science, stress started to be studied at a physiological level, in the decade of 1950. This resulted in a set of reliable physiological indicators for the study of stress, that supported the development of the bio-feedback units available nowadays. In the 70's researchers started studying the somatic disorders resulting from these biologic aspects [14]. At the same time, Hans Selye provided an accurate and simultaneously accessible definition of stress [15], putting forward the notion of stressor and addressing the hormonal changes caused by stress.

Although such views have changed throughout history, there is an agreement that responses to stress are coordinated by a so-called *stress system*, whose composition is nowadays well studied and known to include as main components the corticotropin-releasing hormone and locus ceruleus-norepinephrine/autonomic systems and their peripheral effectors [12]. Moreover, the effects of stress at different levels (e.g. behavioral, peripheral, physiological [16], cognitive) are nowadays becoming known. As a conclusion, an up-to-date view of stress looks at it as a physic-physiologic arousal response occurring in the body as result of stimuli.

A single-modality approach for measuring the effects of stress would thus not be suited, as some experimental results demonstrate [17]. In fact, for a sufficiently precise and accurate measurement of stress, a multi-modal approach must be considered. The diagram depicted in Figure 1 represents a simplified multi-modal view on stress as considered in this paper. This diagram is composed of two main parts: the upper part concerns the predictive aspects of stress while the lower part concerns the diagnostic aspects.

The *Predictive* part of the model considers the following aspects: Context, Profile, Goal and Trait.

Context includes meaningful information to describe the different dimensions of the individual, including the historical, economic, social or geographical contexts. Numerous studies exist that map such information to a base level of stress: the effect of socioeconomic status [18], social or geographical context [19], [20], [21] or individual economic situation [22], just to name a few.

The Profile of the individual includes personal information and characteristics that have an ongoing influence on the level of stress. These include age, gender, marital status, number of dependents [23], type (or lack) of employment [24], job category, among others.

The Goal of the individual at a given moment in time or, likewise, the objectives, aspirations or ambitions also have a significant influence on the level of stress. Namely, individuals with higher ambitions are generally known to be under increased stress, resulting from the continued effort of trying to achieve above average standards [25].

Finally, Trait is related to the personality of each individual, i.e., habitual patterns of behavior, thought or emotion. Some traits are more generally associated with stress than others [26]. As an example, an impulsive individual is generally a more stressed one, with stress driving his hasty decisions.

In the diagnostic part of the model, a larger number of components could be included. Namely those oriented towards psychological or psychosomatic diagnostics, i.e., subjective self-report mechanisms such as surveys or questionnaires. We however focus on objective measures rather than the subjective ones, especially those that can be used to provide real-time feedback. Thus, the *Diagnostic* components of the model include Physical, Physiological, Behavioral and Performance aspects.

Physical aspects include, in a general way, body movements or postures that may have some particular meaning in terms of stress assessment. Especially interesting are aspects such as eyelid movement, facial expressions, body movements (e.g. specific gestures, head movements, repetitive movement patterns) or pupil movement and dilatation

Physiological diagnosis aspects are those that provide the most reliable diagnose of stress. In fact, many approaches exist nowadays that can evaluate the level of stress of an individual from physiological indicators with significant precision, as will be addressed in detail in Section 4.

On the other hand, the behavior of an individual can be seen as the visible end of his inner self. In that sense, aside from other aspects, behaviors (and especially changes in behaviors) may also be a good indicator of stress effects. Given the scope of this paper, particular attention will be dedicated to behaviors when interacting with technological devices or behaviors that can be acquired within technological environments, non-intrusively.

Finally, the Performance of an individual is significantly affected by stress. The optimum level of stress will maximize performance. A higher level of stress may increase performance temporarily but will soon wear the the individual. A lower level of stress will decrease productivity and lead to increasing lethargy. Thus, tests that evaluate performance in given tasks, for which standard performance measurements are known, can be a good indicator of the effects of stress on the individual.

From a high-level point of view, two different types of stress can also be identified: acute and chronic stress. Acute stress comes from recently acknowledged demands and pressures and from anticipated demands in the near future. On the other hand, chronic stress is long-term, due to social or health conditions, dysfunctional families, among many other issues. This type of stress will have nefarious effects on the body and mind of the individual, slowly wearing him away day after day. Acute stress, because it is short-term, won't do the extensive damage associated with chronic stress, although overtime frequent acute stress may contribute to the development of chronic stress. Nevertheless, it will instantaneously influence the performance of the actions being carried out.

Given the broadness of the field, in this paper we clearly focus on acute cognitive stress. Indeed, most if not all non-intrusive and non-invasive current methods for stress assessment are based on the observation of changes on the individual (as detailed in Section 5). When considering acute stress, these changes are easily observed as they constitute significant deviations from an otherwise regular behavior or state [27]. Chronic stress, on the other hand, is more difficult to detect using these means as the individual is constantly experiencing the effects of stress, thus no abrupt changes are observed [28]. We do not mean to imply that it would be impossible to accomplish. However, given the characteristics of chronic stress, its detection using the means explored in this paper would require more extensive data collection about each individual, spanning longer time-frames.

3.2 Stress in the Workplace

As already addressed, stress has effects at many different levels and in many different spheres of our daily lives. Nonetheless, the workplace can be pointed out as a generally stressful environment, especially given today's demands for productivity, competitiveness and performance. For this reason, in this section we analyze the specific characteristics of stress and stressors in the workplace, especially focusing on the causes and outcomes.

3.2.1 Causes

In a general way, a stressor can take many different forms including a chemical or biological agent, environmental condition, external stimulus or any event that forces an organism to adapt to new conditions. Human stressors, in particular, may include environmental factors such as noise or over-illumination, daily stress events such as traffic or lack of physical activity, dramatic life changes such as the death of a relative or a divorce, workplace stressors such as job demands or unrealistic objectives, chemical stressors such as alcohol or drugs consumption, or social stressors such as society's demands/expectations.

When considering the specific issue of stress in the workplace, many theories have been proposed to examine possible causes. Two examples are described below:

- Job demands-control model - this is one of the most widely accepted models to study occupational stress [29]. It considers two main causes for stress (Figure 2): (1) psychological demand of the task and (2) worker's degree of decision/control. (1) includes working pace, difficulty of the task or conflicts at work. (2) includes the possibility to be creative and the autonomy to take decisions about the work and about the work pace. In the 1980s social support at work was added [30]. This deals with the amount and quality of the social relationships at work and their degree of support. The most stressful milieus are, naturally, those with low control, high demand and weak social suppotr, known as high iso-strain jobs [31], [32];
- Job demands-resources model - alternatively, this model regards occupational stress as the result of an imbalance between two main aspects [33]: (1) job demands on the individuals (e.g. physical, psychological, social or organizational aspects of the job that require sustained effort/skills) and (2) resources they have to deal with those demands (aspects that facilitate the achievement of work goals or reduce the cost of job demands, including opportunity for personal development, career opportunities or autonomy). Instead of focusing on the negative outcomes of stress alone, this model considers positive indicators of employee well-being as well (Figure 3).

Less obvious stressors have also been identified and studied by researchers in the last years. A study conducted in 1995 by researchers of the State University of New Jersey, analyzed the impact of electronic performance monitoring and its social context on the productivity and level of stress of employees [34].

Electronic Performance Monitoring (EPM) systems are one of the many technological developments employees face in today's workplaces. These systems provide managers a wide range of information about employees' routines including real-time information such as the pace of work,

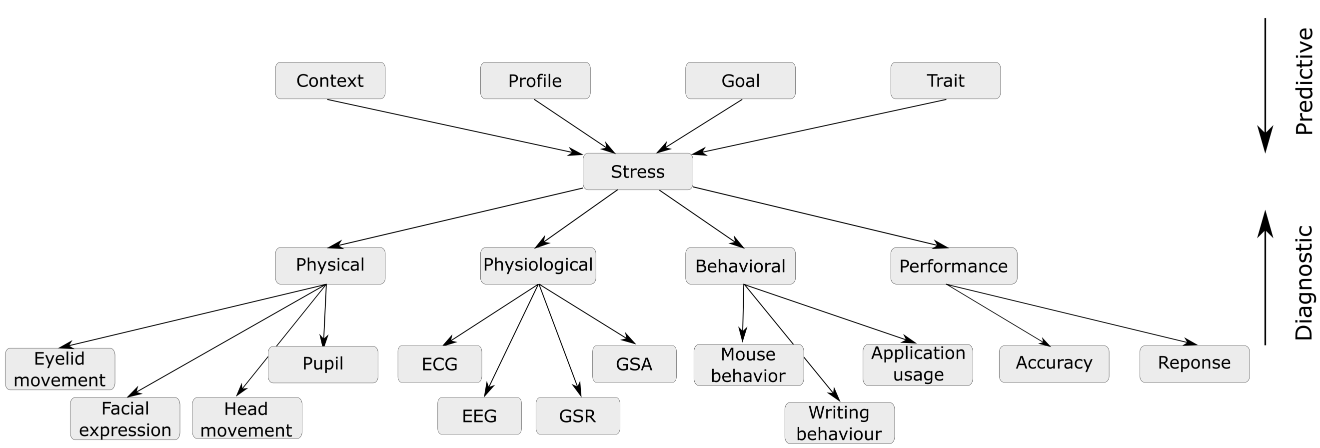

Fig. 1: A possible stress recognition model as viewed in this paper. It includes two main groups of aspects: predictive and diagnostic. Predictive aspects are the ones that can be estimated from the background or context of the individual. Diagnostic aspects are the ones that can be observed and measured and have a relation-ship with the level of stress.

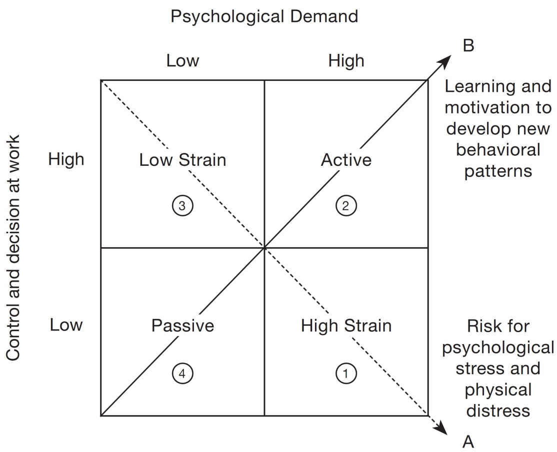

Fig. 2: The job demands-control model [29].

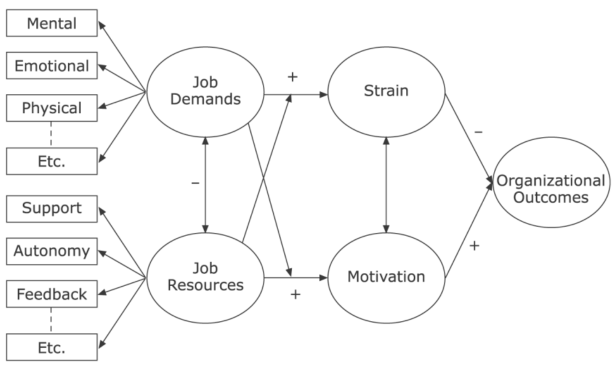

Fig. 3: The job demands-resource model [33].

degree of accuracy, log-in and log-out times, and even the amount of time spent on bathroom breaks. This study examined how productivity and subjective experiences are affected by EPM systems and how the social context of the workplace moderates that influence. In a survey involving the monitored workers, 81% of the respondents declared that electronic observation made their jobs more stressful [35]. Another study compared the behavior of monitored and non-monitored workers who performed similar jobs, and found that monitored workers felt more stressful [36]. The introduction of EPM systems can transform ordinary jobs into high-stress jobs. It can also reduce the opportunities for employees to socialize with each other at work, leading to a loss of social support, partially responsible for the stress associated with EPM [37], [38].

Researchers from the School of Psychology of the University of Liverpool have also analyzed the relationship between stress and productivity in the workplace. The researchers investigated the predictors of productivity using the ”A Shortened Stress Evaluation tool” (ASSET) [13].

The economic and social effects of the existence of stressors have also been studied, with results estimating that each worker experienced an average monthly productivity loss of approximately $200 to $400 due to depression [39]. Similarly, another study estimated that the loss of productivity due to depression has cost American corporations $12.1 billion in 1990 alone [40].

3.2.2 *Outcomes*

The research community clearly acknowledges the existence of a relationship between workspace stressors and mental and physical health outcomes, which is out of our focus. A smaller amount of research is devoted to the effects of stressors on workplace indicators such as productivity.

Albeit sparse, there is some evidences that establishes an association between stress and productivity. Yeh, Lester, and Tauber performed a study on real estate agents that revealed a negative relationship between stress and productivity [41]. Jamal and Baba, using data collected from blue-collar, managerial and nursing employees showed a direct, linear and negative stress-productivity relationship: the greater the stress was, the less productive the workforce was [42].

Several things thus result clearly from this brief analysis: stress in the workplace exists, is increasing with EPM initiatives and other factors, and has negative effects at several levels. Interestingly enough, and given the proven effects on productivity, companies should be one of the interested parties in reducing stress, along with employees who worry about their own health and well-being.

From the analysis of the literature, several causes for companies not implementing active stress management initiatives can be pointed out, namely: (1) their cost; (2) the need for human experts (namely psychologists); (3) possible changes in established work routines; (4) unwillingness of employees to participate (namely when they must talk to other people about their stress-related issues). Many of these issues, if not all, exist due to the characteristics of traditional stress-measuring approaches, which are, as described in the following section, impractical for the workplace.

There is thus the need to study and develop new ways to assess and manage stress that can be effectively used in the workplace, that minimize the disadvantages associated with these traditional approaches. These new methods are surveyed in Section 5.

4 Traditional Approaches

Current stress management techniques in organizations have as a main goal the evaluation of the employees’ state so as to implement approaches that allow them to cope with the negative effects of this phenomena [43]. In a general way, these techniques aim to answer two main questions: (1) to which extent is a given event affecting an employee? and (2) which are the more suited methods to help a collaborator deal with these effects?. The work described in this paper focuses on the first question.

After a state of stress has been identified, different approaches can be followed for its management, including personalized training, support or counseling, group therapy, breathing and relaxing exercises or socialization games. Here, the challenge lies in the choice of the appropriate timing and approach(es). In this process, both the identification of the occurrence of stress as well as the definition and implementation of coping strategies are the responsibility of the organization.

Currently, the use of Human experts in this task represents a cost that often prevents organizations from adhering to these initiatives [44]. Moreover, there are also issues related to limited availability (of both parts), the eventual need for personnel displacements, and the frequent reluctance of employees to discuss their issues in the workplace [45]. An automatized approach, or at least partly automatized, could definitely constitute an important step towards the increase in the adherence to these initiatives.

Traditionally, two main approaches can be followed to quantify the effects of stress: (1) questionnaires or surveys, used mostly by psychology and (2) physiological sensors, used mostly by medical approaches. Each of these approaches has advantages and disadvantages of its own, when considered to be used in a workplace.

Questionnaires, as other self-reporting mechanisms, are seen as an inexpensive approach to collect vast amounts of information. They do not represent a very significant effort for the researcher, who also benefits from the easiness in compiling data, which results from a set of predefined answers [46]. These instruments are eminently practical and can be administered either by the researcher or by anyone else, possible remotely, without affecting validity or reliability.

They have, however, a number of disadvantages that go beyond traditional problems related to the definition and formulation of questions [47]. They are based on individual perceptions of rather subjective concepts such as *good*, *poor*, *big* or *low*. It is also easy for a participant to (unconsciously) hide information, voluntarily lie or depreciate/over-valuate certain indicators [48]. This type of behavior is virtually unidentifiable by the researcher. Finally, at the moment of developing the questionnaire, researchers take their own decisions and assumptions concerning what is or is not important. Consequently, even if an individual considers a certain issue as being very important, there is no efficient way to express this if no specific questions regarding this issue exist in the questionnaire.

Nonetheless, many questionnaires and other instruments exist for stress assessment in many different domains (e.g. trauma, family, occupational), which have been validated and used thoroughly over the last decades. Specific instruments exist for the workplace and similar milieus. Some widely used instruments include the 30-question ”Perceived Stress Questionnaire” [49], the ”NIOSH Generic Job Stress Questionnaire”, including psychosocial measures such as mental demands, perceived control, workload or job ambiguity [50] or the ”Copenhagen Psychosocial Questionnaire” (COPSOQ), a comprehensive instrument for the assessment of psychosocial work load and strain [51]

Technological advances and medical research lead to a more accurate approach to the problem, based on a range of sensors that measure physiological or neurological effects of processes such as stress, fatigue or emotions on the human body. Please note that in this section we are analyzing the more traditional applications of physiological sensors, tendentiously in the medical context. For more recent applications of these kind of technologies please refer to Section 5.

In this field, one of the most precise indicators is the adrenocorticotropic hormone (ACTH): a hormone produced by the pituitary gland, located below the brain. ACTH activates glands on the kidneys (adrenal glands) to make cortisol. Cortisol has many functions: it helps the body use sugar (glucose) and fat for energy (metabolism), and it helps the body manage stress. Cortisol levels can be affected by many conditions, such as physical or emotional stress, strenuous activity, infection, or injury. When cortisol levels in the blood rise, the ACTH levels in a healthy person normally fall in response.

Cortisol can be measured in saliva, hairs or blood [52]. Assessment of cortisol in saliva is an especially widely accepted and frequently employed method in psychoneuroendocrinology [53], due to several advantages over other analyses (e.g., stress-free sampling, laboratory independence, lower costs) [54].

Nonetheless, other sensors or combinations of sensors, measuring other physiological manifestations, can be used for similar purposes. The rationale behind the analysis of physiological signals to study inner states of an individual is based on well-known associations between two main divisions (parasympathetic and sympathetic) of the Autonomic Nervous System (ANS) and numerous physiological processes around the body [55]. The ANS influences the cardiovascular, respiratory, digestive, urinary and reproductive functions. The parasympathetic division of the ANS stimulates visceral activity and promotes a state of rest in the organism. In contrast, the sympathetic division of the ANS prepares the body for heightened levels of somatic activity that may be necessary to implement a reaction to stimuli that disrupt this state of rest. The sympathetic division is thus responsible for the well-known flight-or-fight response, which prepares the body for a scenario that may require sudden, intense physical activity [55].

Skin conductivity, for instance, measures the skin resistance to electric current, which varies according to the level of perspiration. Given that sudoriparous glands are controlled by the sympathetic nervous system, they unveil mental states associated with psychological or physiological arousal, which take place during peaks of stress. Likewise, boredom states can also be detected. Skin temperature, heart rate or respiratory rate are also well-known indicators for the study of stress, emotions or fatigue [55], [56]. Heart rate variability, defined as the variation of the time between heartbeats, has been increasingly used to study stress [57], showing that both are closely connected [58].

The steep growing of biofeedback tools in the last years is also worthy of note. These tools combine feedback from multiple bodily functions, using instruments that analyze indicators such as brain waves, muscular response, skin conductivity, heart rate, pain perception, among others [59]. The study of brain waves is particularly interesting since it provides clues about aspects such as fatigue, levels of stress, arousal or emotional state in a very thorough way, also allowing to compare, at the same time, other related (or not) phenomena. Biofeedback tools can also be used to improve certain aspects such as daily habits or behaviors, since they provide real-time feedback to the user about the consequences of their attitudes, decisions or behaviors [60].

In a general way, approaches based on physiological sensors can be seen as very precise and are used not only to evaluate the state of an individual but also as a basis for medical treatments and intervention. Their use, validity and utility are nowadays acknowledged by research initiatives and medical applications alike [55], [56], [61], [62]. However, in the context of this work, both approaches (physiological sensors and questionnaires) are looked at considering their use in a real workplace. In that sense, it becomes necessary to ascertain the extent to which these approaches are suitable to evaluate the state of an individual in these milieus. Our conviction, based on the rationale detailed below, is that such approaches are not suitable.

When people use a questionnaire to describe themselves or some of their behaviors, it may happen that their views or opinions do not exactly fit the possible answers. To deal with this issue, individuals often decide not to answer or use the option that, in their view, more closely relates. Doubts about the quantification of the answers are another frequent problem. While some of the frequently used concepts, such as *never* or *always*, are easy to define, others such as *frequently* or *occasionally* are less clear. When these questionnaires concern the behavior of the individual in a given situation (e.g. "How would you react if, feeling incredibly tired, you were given a task to complete in a short time frame?"), there is no guarantee that the behavior of the user in the actual situation would match the answer. That is, individuals answer how they *believe* they would or do behave. Nonetheless, stress is partly a subjective psychological experience, i.e., it depends on how each individual interprets and copes with stressors. From this point of view, self-report mechanisms are still interesting.

When, alternatively, physiological sensors are used, the main and most immediate drawback is that the individual may feel uncomfortable (Figure 4). This may result in refusal to participate, especially in cases in which the use of sensors involves wires and other hardware that may limit movement. All these factors make it more difficult to collect the data. On the other hand, there may be an undesirable effect on the variables under study caused by the monitoring itself: the simple fact that the individual is connected to sensors may increase stress, consequently affecting the results.

These problems can be briefly analyzed through some specific examples. [63] present an approach based on four different sensors to detect stress in a non-invasive way. Nonetheless, the method is highly intrusive as the participant cannot move the left hand. The work described in [55] uses, in addition to physiological sensors, a video-based eye tracking gazing system, which poses an additional drawback concerning privacy. Many other examples can be found with very different physiological markers (e.g. galvanic skin response in both feet and hands, heart rate variability, electrocardiograph signal, electromyography signal) [56], [61], [64] and in different domains of application (e.g. stress in students during exams, stress in drivers) [65], [66]. The problems do however remain: these approaches, although undoubtedly accurate and usable in real-time, have many and significant effects on the routines of the individuals. None of these so-called traditional approaches can be used, in a realistic manner, to quantify the level of stress of an individual in a workplace. At least, they cannot be used without changing established work routines or without interfering with the individual.

Given this, the following sections detail a new paradigm for the acquisition of valuable information for stress assessment in which the focus is on the behaviors of the individuals, looked at as mirrors of their inner states. In fact, processes such as stress, fatigue or emotions have measurable effects not only on our physiology but also on our observable behavior: a healthy individual is able to look at someone and identify these signs, in an innate way. If we provide computer systems with the ability to identify and quantify such behaviors and, if a relationship is established between these behaviors and certain mental states, the door is open to the development of non-intrusive methods for the classification of the state of individuals based on the observation of behavioral indicators. This is the goal that motivates the work described in this document.

5 New Methods for Stress Assessment

New methods for stress assessment were developed in the last years as a result of an unprecedented evolution in consumer electronics and miniaturization. Others were made possible from a better understanding of stress and its effects on the Human being at several levels: physiological, behavioral or physical. The diversity of alternatives, as shown in this section, allows for solutions to be used in specific scenarios with increased accuracy and commodity (e.g. driving vehicles, working at the computer). In this section we analyze in detail the characteristics of each of these new methods and in Section 6 we provide a critical analysis and a comparison between them.

5.1 Wearables

One of the latest trends in stress management is being fostered by wearable devices. Indeed, in the last years there was a major development in consumer electronics, with devices being used for acquiring physiological signs. They

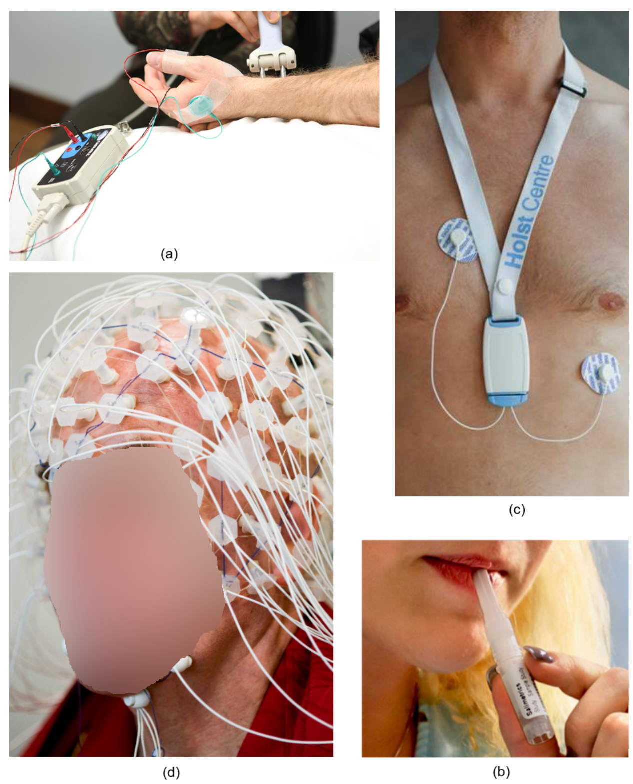

Fig. 4: Several traditional approaches for stress monitoring: (a) electromiography, (b) salivary cortisol, (c) heart rate variability and (d) electroencephalogram.

constitute more comfortable approaches than the traditional sensors mentioned in Section 4 as they can be worn, as a regular fashion accessory or clothing (Figure 5). They have, thus, some advantages.

Chan et al. provide a thorough overview of the extensive efforts made in both academia and industry in the research and development of smart wearable systems for health monitoring [67], their driving forces and their future impact in healthcare industry. Choi and Gutierrez-Osuna [68] address this issue in a general way, describing the development of a wearable sensor platform to monitor physiological correlates of mental stress for ambulatory stress monitoring. The work relies on a Wireless Body Sensor network with spectral features that estimate the balance of the autonomic nervous system by combining information from the power spectral density of respiration and heart rate variability.

While the two previously mentioned works are rather generic, specific examples of application can also be found. In [69], the authors analyze the discriminative power of electrodermal activity in distinguishing stress from cognitive load, using a wrist-worn device, with sensors placed in strips attached to two fingers. In [62] the authors also present a wearable system for assessing stress, sensible to the task being carried out by the user so that the user does not need to necessarily sit in a chair, as usual. Similarly, [70] presents AutoSense: a wireless sensor suite that collects and processes cardiovascular, respiratory, and thermoregularity measurements that can inform about the general stress state of test subjects in their natural environment.

Finally, the work detailed in [71] presents a stress management biofeedback mobile service for everyday use, aiding users to reflect on both positive and negative patterns in their behavior. To accomplish this the authors also developed a wearable set of sensors that facilitate data acquisition and analysis. The main difference from the previous works is the development of the biofeedback mobile service that, through a set of intuitive interfaces, aids the users in perceiving the effects of stress on their daily lives.

Fig. 5: New approaches for taking stress-related measures, based on wearables: (a) a chest belt, (b) a onesie for tracking babies' vitals and (c) a wrist band.

5.2 Smartphones

The evolution witnessed in the field of smartphones in the last years also led to the emergence of a new paradigm: wellness mobiles. Technological developments make it possible for health-care professionals to have access to comprehensive real-time patient data. Likewise, users can also continuously track their health on the go, build a comprehensive history and receive real-time advice or warning [72]. Indeed, mobile phones have a growing number and variety of sensors that can nowadays be leveraged to produce, in the near future, what can be called as personal wellness dashboards: devices with the ability to measure our heart rate or body temperature and quickly analyze our state of health. This may make personal health care cost-effective, decreasing the use of emergency care [72].

Some mobile apps take advantage, to some extent, of the sensors currently present in smartphones (Figure 6). Although, in many cases, some of these apps lack proven scientific validity, their low cost and their availability makes them easily reach a significant number of users.

The majority of existing apps use the smartphones' built-in sensors. Azumio's Stress Check uses the camera and light features of the smartphone to measure heart rate. A similar approach is followed by other apps (e.g. StressViewer). There is also a significant amount of apps dedicated not to measuring stress but to decreasing or coping with it, namely through breathing exercises, with visual or sound aids. Stress Releaser is one such app. Another example is DeStressify, that is based on music and specific exercises.

There are also apps that use specific hardware, such as PIP Relax and Race, which is based on an electrodermal activity sensor. In this specific app, the user takes part in a race where victory is achieved only by out-relaxing the opponents. A generally competitive activity is thus changed into a relaxing one, with real-time biofeedback. Similar apps exist for this specific hardware. DroidJacket [73] requires the use of VitalJacket - a shirt that embeds an electrocardiogram sensor, allowing a continuous monitoring of the patient. The work described in [74] also uses a specific sensor platform (Personal Biomonitoring System), in parallel with the smartphone, to monitor the level of stress of the smartphone user.

Other smartphone-based approaches are based on the changes in the speech production process, that happen during stress. To this end, these applications use the microphones embedded in the mobile phones. StressSense [75] is one of such applications, based on a classifier that can robustly identify stress across multiple individuals in diverse acoustic environments.

There are also authors who look at the behavior of smartphone users for stress indicators. Although not in a conclusive manner, in [76] the authors find significant differences in location traces, visible bluethooth devices and phone call patterns when comparing stressful with stress free periods.

5.3 Computer Vision

Many different image sources can be used to monitor stress, the most frequently used being the Human face. Although cultural differences can intensify facial expression of emotions, there is considerable scientific evidence that emotions are communicated in distinct facial displays across cultures, age and gender [77]. These approaches can be classified as two-dimensional or three-dimensional. Their main difference is that the first tries to recognize features directly from a two-dimensional decomposition/transformation of the image, and is generally not sensible to rotations and translations of the face.

In [77], the authors apply optical computer recognition algorithms to detect facial changes due to low and high-stressor performance demands, with the aim to develop an approach suitable to be used by astronauts. This approach takes as input images from the whole face. On a similar approach but on a different field of application, Gao et al. present a system for detecting stress from facial expressions in car drivers [78]. Barreto et al., on the other hand, consider only pupil diameter (together with physiological signals), to assess stress [55], [63]. To this end, they make use of a specific camera-based eye-tracking system.

Other authors simultaneously look at groups of features extracted from the face. In [79] an approach is presented based on what the authors call "physical appearance": facial expression, eye movements and head movements. These features are used together with physiological signs and behavioral data to assess the level of stress of a computer user. Thermal imaging can also be used [80], namely to measure blood perfusion in the orbital muscles, which correlates to

Fig. 6: Android apps for measuring stress, with and without additional hardware: (a) Stress Check, (b) Droid Jacked [73] and (c) Stress Tracker [74].

stress. These approaches are however prone to error when certain types of light or heating systems are used.

There are also authors who look at sequences of images to search for signs of stress. Giakoumis et al. analyze video and accelerometer information to extract activity-related behavioral features and perceive signs of stress [81]. Sharma et al. also consider video analysis, using both temporal thermal spectrum and visible spectrum video features, which they make available as a database - ANUStressDB [82].

5.4 Speech and Other Linguistic Features

This section describes approaches for stress assessment based on vocal cues such as speed, rhythm or intonation. Interestingly, the variability introduced by stress or emotion can severely reduce speech recognition accuracy. Thus the importance of techniques for detecting or assessing the presence of stress to improve the robustness of speech recognition systems [84].

In [85], the authors present a hierarchical framework, which consists of three layers of classifiers, for automatic stress detection in English speech utterances: a linguistic classifier, an acoustic classifier and an AdaBoost classifier. The paper presents accuracy rates higher than 90%.

In a related approach, Imoto et al. address sentence-level stress detection of English for Computer-Assisted Language Learning by Japanese students. Stress models are set up by considering syllable structure and position of the syllable in a phrase, providing diagnostic information for students [86].

There are also approaches based on prosodic or acoustic features. Xie et al. present an approach for the automatic

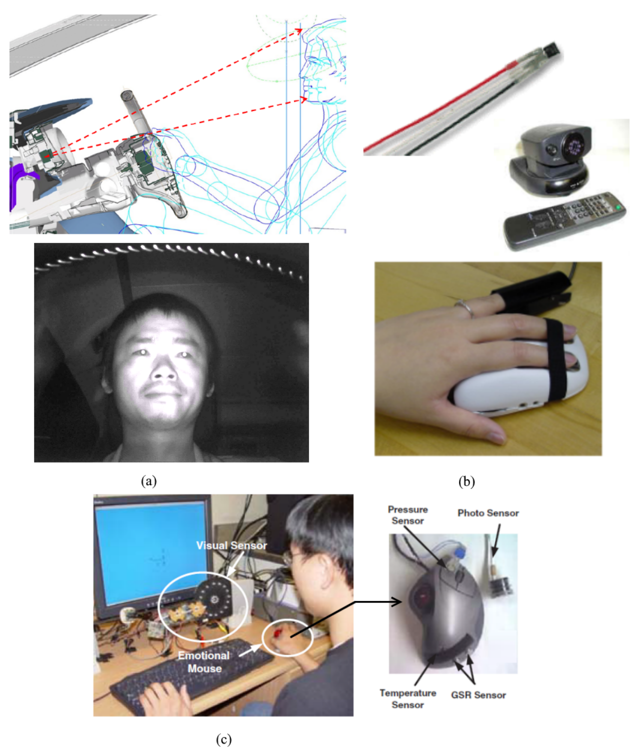

Fig. 7: Approaches based totally or partially on computer vision: (a) detecting emotional stress on drivers [78], (b) stress detection in Human-Computer Interaction through gaze detection [83] and (c) stress detection using a visual sensor and an emotional mouse [79].

detection of rhythmic stress in spoken English, based on speaker independent prosodic features and vowel quality features as terminals to classify each vowel segment as stressed or unstressed [87]. Similarly, in [88] an English lexical stress detection approach using acoustic features is proposed. The feature set includes the semitone, the duration, the loudness and the emphasis features.

5.5 Computer Mouse

In this section we analyze a group of approaches that can be deemed as non-intrusive as they rely on the usage of the mouse, requiring no specific additional hardware. This approach can thus be included in the so-called Mouse Dynamics field.

Different mouse-based approaches can be implemented. On the one hand, it is possible to build sensors into the mouse, which collect physiological signs when the user is in contact with the mouse, as proposed in [79]. Photo, pressure, temperature and galvanic skin response sensors were integrated in a mouse, allowing them to determine when the user is using the mouse and acquire physiological variables that correlate to stress. On a similar approach, the authors of [89] developed a capacitive mouse that measures the amount of hand contact with the mouse, allowing the authors to estimate the pressure exerted on the mouse. The authors conclude that mouse contact is significantly higher when participants are under stress.

Other authors have looked at the mouse and its usage in search for different stress correlates. Namely, [90] look at how the users *move* the mouse and propose a simple model of arm-hand dynamics that captures muscle stiffness during mouse movement. Other authors have also extracted behavioral features from mouse usage, such as in [91], extracting features such as mouse speed, inactivity, or mouse click rate. Finally, features extracted from the mouse have also been shown to be related to stress measures during exams [92].

5.6 Computer Keyboard

The keyboard of the computer is also being researched as a way to assess the effects of stress. One of the most frequent approaches relies on Keyboard Dynamics, which looks at the behavior of the user while typing through features such as key latency or writing speed [93].

Such an approach is followed in [91], in which the authors consider three keyboard features: average key latency, average typing speed and occurrence of error keys. In [94] the authors also use seven behavioral features extracted from the keyboard, but rely on a Case-based Reasoning system for stress classification.

Specially designed keyboards have also been developed to extract additional features that regular keyboards do not provide. In [89], the authors present a pressure-sensitive keyboard that provides, for each keystroke, a value of pressure between 0 (no pressure) and 255 (maximum pressure) (Figure 8). The authors conclude that the pressure on the keyboard is significantly higher under stress.

Finally, there are also keyboard-based approaches that incorporate the linguistic features of the written text. In [83], the authors combine keystroke and linguistic features of spontaneous generated text, measuring physical and cognitive stress.

Fig. 8: A regular mouse and keyboard can be used to assess stress through behavior. This hardware can also be modified to provide additional features. The image depicts a pressure-sensitive keyboard and a capacitive mouse [89].

6 Critical Analysis

6.1 Methods

Section 5 showed that there are many novel methods to assess stress. However, all these different methods have characteristics of their own, as well as unique advantages and disadvantages.

Wearable devices incorporate physiological sensors in clothing or accessories, constituting a very convenient alternative to traditional physiological sensors, although the person still has to 'wear' the device. The battery life is nowadays relatively large, often allowing the device to be worn for several days. One of the key advantages of these approaches is that they can integrate physiological signs whose relationship with stress is nowadays well-known and thoroughly studied (e.g. heart beat, respiratory rate, body temperature). This means that very accurate approaches can be implemented. The main drawback of these approaches is their price, since these devices tend to have a significant cost.

Most of the existing smartphone-based approaches for stress assessment rely on the use of the integrated flash to measure heart rate and provide a quantification of the level of stress. This approach has a lower accuracy than wearable devices, in part because it is based on a single physiological sign. Moreover, in order to continuously collect data over long periods of time, the user would have to constantly touch the light of the smartphone, which is impracticable. This type of solution is thus more suited to periodic analyses. On the other hand, the main advantage of these approaches is that they can be used by anyone who already owns a smartphone, generally by just installing a simple app that also makes the logging, visualization and sharing of information very easy. Nonetheless, the evolution of smartphones, namely through the inclusion of additional sensors, may open the door to more accurate approaches. Smartphones have, undoubtedly, a significant role to play in the future of personal healthcare.

Some of the most well-studied approaches to stress detection are based on video-cameras. Many algorithms are known nowadays which not only detect or quantify stress but also assess emotional state and other cues. The cost of these approaches can vary significantly, depending on the quality of the video camera used. Moreover, they tend to only be accurate when the user stares frontally at the camera and with proper lightning conditions. Under these conditions, video-cameras can prove useful and comfortable in assessing stress, since the user does not need to be connected to sensors or do any specific task. However, the user does need to remain relatively still and face the camera directly. For this reason, these approaches are mostly directed at tasks with these characteristics, such as working with a computer or driving a vehicle. Nonetheless, the most negative aspect of this approach concerns privacy. Indeed, people often dislike being monitored, especially in the workplace and in such a direct way, which may, by itself, influence stress levels.

Speech- and linguistic-based approaches face a similar drawback as users may look at the monitoring of their speech or their words as an invasion of their privacy. To cope with this, people often change their normal behaviors (e.g. avoiding conversations that they would usually have), thus undermining the process itself. While some features do take into account specific words and may pose these problems, others are based on *how* the person talks rather than on *what* the person talks (e.g. speech rhythm). These features should thus be preferred and the users should be made aware of their characteristics in order to increase acceptance. Other than that, these approaches are generally inexpensive as they are based either on written text or on speech acquired though a microphone, which can be embedded in existing devices, such as in the case of smartphones. They do, however, require that the person speaks or types text in order to produce a result. For this reason, they tend to be more suited to specific domains (e.g. call centers).

Finally, approaches based on computer peripherals also constitute inexpensive and interesting ways of assessing stress. The main drawback is, evidently, that they can only be used in domains in which people interact with a computer. They are thus directed at environments such as laboratories, workplaces or academia. People also often express concerns with these kind of logger applications that register all that is done with the mouse and the keyboard. The most important step to take regarding this concern is to focus on features that (as with speech-based approaches) do not consider *what* is written but *how* it is written. Similarly, when considering the mouse, features should focus on how people click or move the mouse rather than where people clicked or moved to. Fortunately, if some of the linguistic features are left aside, most of the features extracted from the mouse and the keyboard pose no concerns in this regard. The strongest aspects of these approaches are: (1) a very low cost since they are generally based on existing and inexpensive hardware; and (2) the diversity of features that can be extracted which, depending on minor hardware modifications, may include physical, behavioral and physiological measures.

Table 1 presents a summary of the characteristics considered to assess each stress assessment method and a score (1 - lowest, 5 - highest) that allows for an intuitive comparison. The following characteristics were taken into consideration:

- Versatility - Quantifies how fit the method is to be used in different domains;
- Cost-effectiveness - The cost-effectiveness of the method (e.g. additional hardware, cost of associated software). The value 1 denotes a low cost-effectiveness, i.e., a more expensive method;
- Intrusiveness - Quantifies the extent to which the routine of the individual is affected by the stress assessment method. The value 1 denotes that the method is very intrusive while the value 5 denotes that it is completely transparent to the user. For example video cameras or keyboard are not considered intrusive since their use for the purpose of stress monitoring does not have an effect on work routines;
- Feature Diversity - While some methods provide a small number of features or features from a reduced number of modalities (e.g. physiological, behavioral, physical), others give access to a larger number and variety. Multi-modal approaches generally hold potential for increased performance;
- Specific Hardware - Quantifies the degree to which specific additional hardware is required for the method to assess stress. The value 1 denotes that a significant amount of additional hardware is required for the method to be used while the value 5 denotes that no additional hardware besides what is available in a general scenario is necessary;
- Availability - Determines to which extent the method is easily available, from the point of view of the user. As an example, simply downloading an application is very convenient;
- Privacy - Quantifies the extent to which a given method can constitute a potential threat to privacy. The value 1 denotes a potentially threatening method;
- Richness - This characteristic compares the methods in terms of the richness of analysis that can be combined in a single device. For example, a smarphone allows the acquisition of behavioral, physical and physiological features;
- Accuracy - Denotes, in a general way, the accuracy of the approaches concerning stress classification.

	Versatility	Cost-effectiveness	Intrusiveness	Feature Diversity	Specific Hardware	Availability	Privacy	Richness	Accuracy
Wearables	5	1	4	5	1	3	5	3	5
Smartphones	3	2	3	5	3	5	5	5	3
Computer Vision	2	1	5	3	2	3	1	2	5
Speech & Linguistic	2	4	5	3	4	5	2	2	4
Mouse	2	5	5	4	5	5	5	3	3
Keyboard	2	5	5	4	5	5	5	4	4

TABLE 1: Comparison of the different methods studied for stress assessment.

The data displayed in Table 1 can be graphically summarized to allow a more intuitive interpretation. Figure 9 shows how each of the methods studied scores in each of the 9 categories evaluated. Through this graphical representation, the methods can be compared using the area of the radar plot. Thus, in the overall, the best method for stress assessment in the workplace, according to the analysis carried out, is the keyboard, with a score of 54.32 (out of a maximum value of 72.48). Likewise, the worst methods for this purpose are those based on computer vision, mostly due to their privacy concerns, cost and requirements in terms of hardware. Figure 10 details and compares the score of each method as well as the maximum possible score.

6.2 Characteristics

It is likewise interesting to conduct this analysis from the point of view of each of the characteristics studied (especially in cases in which one or several characteristics are more important than others). Figure 11 supports this kind of analysis.

In terms of versatility, methods based on smartphones and wearables are those that score higher, especially in the case of wearables. Wearables can provide a wide range of physiological measures, as well as other features extracted from hardware such as accelerometers. In the case of smartphones, their versatility comes from the ability to develop specific and custom applications, that use not only the built-in sensors but also external hardware (e.g. heart rate monitors).

In what concerns cost-effectiveness, methods based on the keyboard and mouse appear as the best, followed closely by speech and linguistic. Indeed, these computer peripherals are common in modern workplaces, especially those linked to the so-called 'white-colar' jobs, and their cost is nowadays very low, making them a cost-effective approach for continuous and non-intrusive stress assessment.

Of all the characteristics considered, intrusiveness is the one that achieves a higher score, i.e., the one that is more broadly contained in all methods. Apart from smartphones and wearables (in which people need to perform a specific action or wear a specific fabric), stress is assessed from the regular actions of the individual with the devices in the environment. This makes these methods highly transparent and unobtrusive.

Feature diversity also scores relatively high, especially due to the contribution of smartphones and wearables, which can provide a rich set of features for stress assessment.

Considering the need for additional/specific hardware, the best methods are, once again, those based on keyboard, mouse or speech. Indeed, when considering modern workplaces, the mouse and the keyboard are nowadays common. The same is almost as true for microphones since most of our laptops or smartphones have embedded microphones that can be used for stress assessment. For these reasons, this characteristic has a very similar score to cost-effectiveness. On the other hand, methods based on computer vision require video cameras, smartphones may require additional sensors or hardware and methods based on wearables necessarily require specific hardware, contributing to worse scores.

In terms of availability, the highest scores belong to methods based on the smartphone, keyboard, mouse and speech. This is due to the fact that these devices are nowadays easily available and that it is only necessary to install a specific software to start assessing stress.

Concerning privacy, the highest scores are attributed to smartphones, wearables and computer peripherals. In

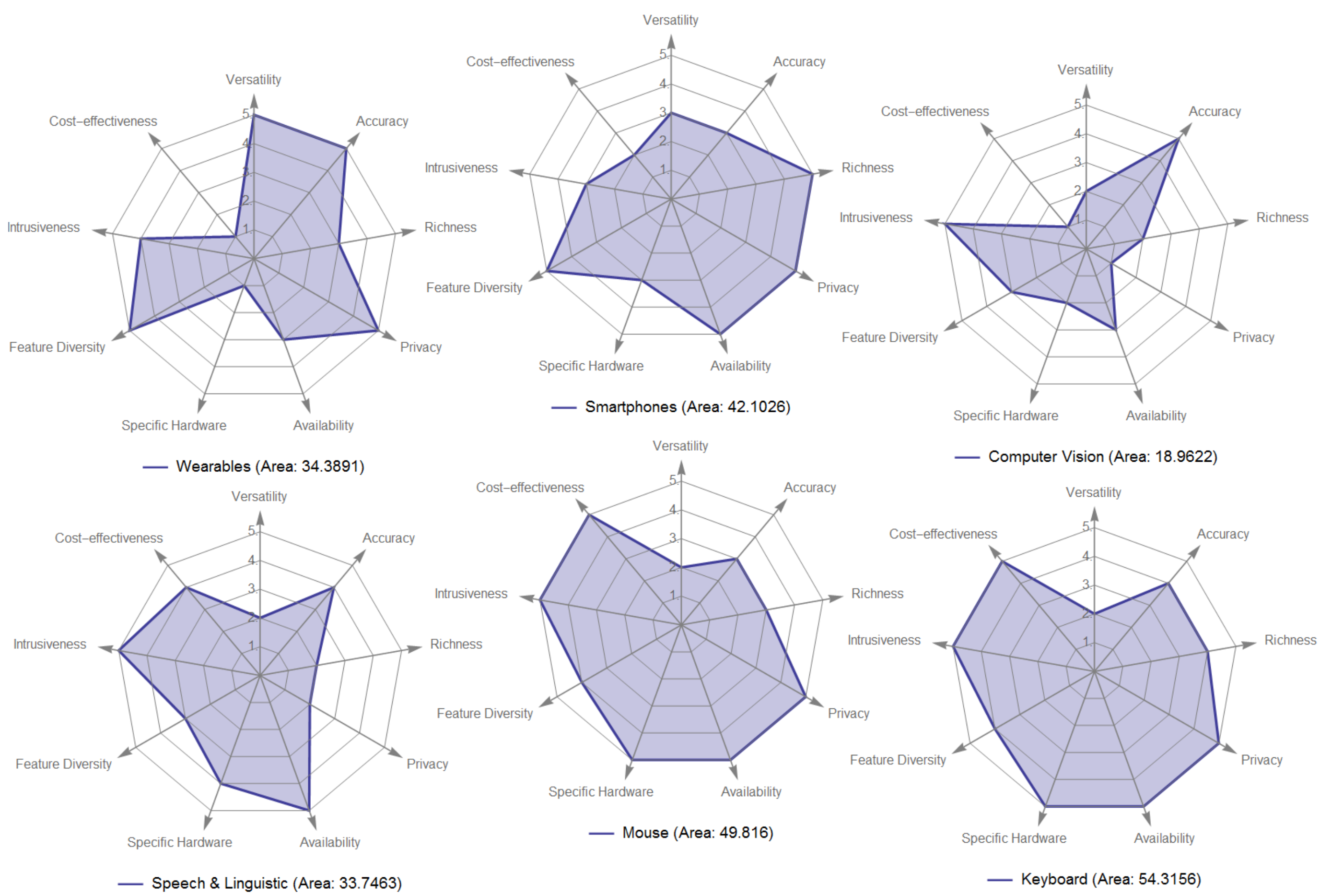

Fig. 9: The score of each method in each of the 9 characteristics evaluated.

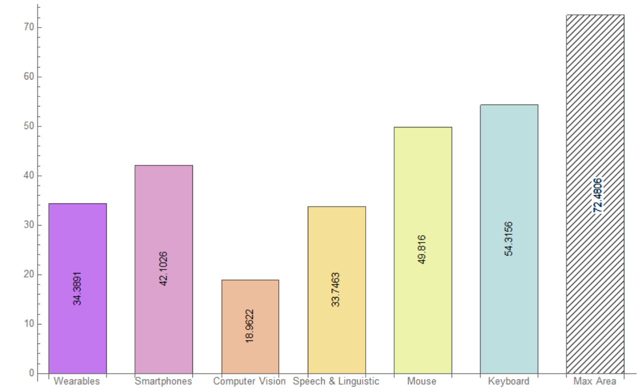

Fig. 10: Score of each method studied, as well as the maximum score.

the case of the first two, these devices are tendentiously personal, which gives the user increased confidence on their use. In the case of computer peripherals, they can be used to assess stress in a safe way, i.e., without actually knowing what the person is typing or where the person is clicking. Speech- and video-based approaches score lower in terms of privacy. The former mostly because the user needs to speak out in order for the stress assessment to take place. The latter mostly because of all the privacy-related issues associated to the use of video cameras, especially in the workplace.

In terms of the richness of the analysis that each method allows, the methods based on smartphones and on peripherals are the ones that achieve highest scores. The score is especially high since it may provide access to features of different modalities, including behavioral (namely application usage), physical and physiological. Similar statements can be made about the mouse and the keyboard.

Finally, in terms of accuracy, the methods that achieve the best scores are those based on computer vision and on wearable devices, especially the ones incorporating physiological sensors, which are among the most accurate approaches to assess stress.

Pointing out an ”absolute best” method is rather impossible as this always depends on the characteristics and constraints of each specific setting. However, and focusing on the specific problem of stress assessment in the workplace, the methods that achieve generally best results are those based on mouse and keyboard, also achieving good scores on characteristics such as cost-effectiveness, intrusiveness, need for specific hardware, availability and privacy. These conclusions, however, apply mostly to office-type jobs, in which people sit at the computer for a significant part of their workday. When considering other jobs, alternative methods could be more appropriate. As an example, smartphones or wearables are a more suited method to assess stress in health professionals.

6.3 Stress Modalities

Alternatively, these methods can also be analyzed from their multimodality, i.e., their ability to capture stress effects in their different modalities. The underlying assumption is that a method that can measure effects from multiple modalities is, expectedly, more accurate than a method based on a single modality. The modalities considered are those put

	Physical	Physiological	Behavioral	Performance
Wearables	2	5	2	1
Smartphones	2	3	4	4
Computer Vision	4	2	2	1
Speech & Linguistic	1	1	4	1
Mouse	2	2	5	5
Keyboard	2	1	5	5

TABLE 2: Score of multimodality.

forward in the diagnostic part of the model presented in Figure 1: physical, physiological, behavioral and performance. We score each method (1 - lowest, 5 - highest) according to their ability to produce features from each of the four modalities put forward in the model (Table 2).

Wearables score the highest in the physiological modality. Indeed, these methods are mostly based on physiological sensors that can be placed directly on the body of the individual, ensuring a continuous monitoring of physiological signs. These methods can also provide some information regarding physical/behavioral modalities, mostly through accelerometers, allowing the acquisition of features such as movement patterns, activity levels or activity classification.

Smartphones stand out especially in the behavioral and performance modalities. Behavioral features are acquired from aspects such as application usage patterns, user location or from the accelerometer or gyroscope of the device. Concerning performance, smartphones can provide features such as accuracy measures or response times, namely through the use of specific or modified applications. Physiological measures can also be acquired from a smartphone, either from the built-in camera or from additional sensors. Finally, smartphones can also provide some physical features such as the intensity of the touch on the screen or the acceleration measured on the device when the user is interacting with it. All this makes smartphone-based methods one of the most multimodal ones.

Methods based on computer vision are essentially directed at physical measures, including eyelid movement, facial expressions, head movement, or pupil dilatation. Nonetheless, some features from physiological and behavioral modalities can also be extracted. As an example of the physiological modality, a group of researchers from MIT’s Computer Science and Artificial Intelligence Lab (CSAIL) showed that it is possible to measure human heart rate and heart rate variability in ordinary video footage. In what concerns the behavioral modality, methods based on computer vision allow the analysis of aspects such as changes in focus (attentive behavior) or gaze detection.

Methods based on speech and linguistic features are among the more limited ones in terms of the diversity of modalities. Indeed, these methods provide access to mostly behavioral features.

Finally, there are the two groups of methods based on the computer peripherals (mouse and keyboard), which are among the most multimodal ones and achieve similar scores. The highest scores of these methods are achieved in the behavioral and performance modalities. To some extent it is also possible to extract physical features from these devices, especially in what concerns physical fatigue from long periods of use. Moreover, some of the features that we associate here with behavior are, in part, also influenced by physical aspects of the individual (e.g. development of certain muscles, elasticity of certain tendons). Finally, we also surveyed some works in which researchers modified the standard keyboard and mouse to provide physical/physiological features (e.g. pressure sensitive keyboard, capacitive mouse).

The score of multimodality of each method can thus be computed, as done before, by calculating the area of the radar chart for each method, as shown in Figure 12.

7 Discussion and Future Trends

From the papers surveyed in this document, one first conclusion is evident: there is nowadays an unprecedented diversity in methods for stress assessment. Until a few years ago, stress assessment would be carried out through questionnaires or through invasive or even intrusive approaches. While these are suited for medical interventions or treatment, they are not adequate for more modern applications, in line with Ambient Intelligence and the paradigm of personal healthcare. Especially, and if we keep in mind the scope of this research line, they are not suited to be used in the workplace, in which the aim is to monitor continuously and in real time, without interfering with the worker's routine.

Another conclusion is that existing non-intrusive/non-invasive methods are more suited to measure acute stress than chronic stress, as pointed out at the end of Section 3. It is also a fact that it is really the chronic stress that costs companies billions of dollars and hurts workers the most [28]. This could result, at a first glance, in the deeming of the surveyed methods as inadequate or insufficient to solve the addressed problem. However, it must be kept in

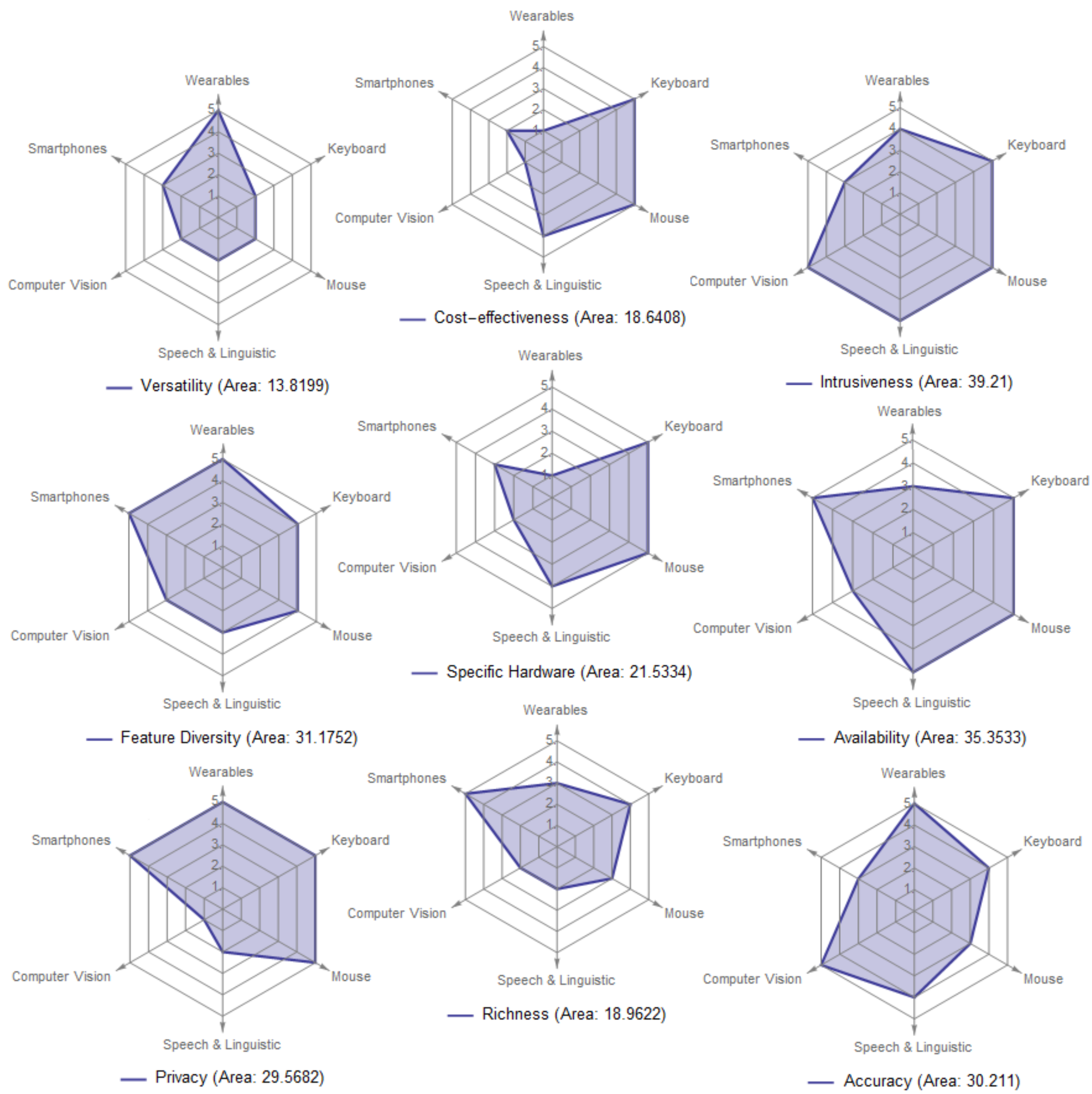

Fig. 11: The extent to which each of the characteristics studied is contained in each method.

mind that chronic stress occurs, among other issues such as exposure to traumatic events, in response to frequent everday stressors that are ignored or poorly managed. Thus, it is our conviction that the surveyed methods may have an important role in the process: helping to prevent the actual occurrence of chronic stress by supporting the identification and management of everyday peaks of acute stress.

On the other hand, consumers are nowadays very keen on inexpensive methods to monitor and log their health and well being. These methods can be implemented with the support of smartphones and other similar devices which, by themselves or with the support of additional hardware, can collect information about the user. This may, however, fall short. While smartphone-based approaches are still limited, namely in terms of the features that they collect, they require users to stop what they are doing in order to take a measurement (e.g. placing a finger on the light of the smartphone to measure heart rate). Moreover, they require the user to consciously engage in the process.

Other very different approaches can also be implemented nowadays, namely based on video cameras, microphones or wearable devices. These approaches are, undoubtedly, suited to assess stress in certain domains. Video-based approaches are especially suited to vehicle driving as they can accurately point out driver stress or fatigue, mainly because the driver must look ahead at all times, thus constantly facing a frontally placed camera. However, such approaches are not suited to the common workplace, for two main reasons: (1) they require at least one camera per person, which makes them expensive; (2) they are seen as a privacy-threatening and may acquire images even

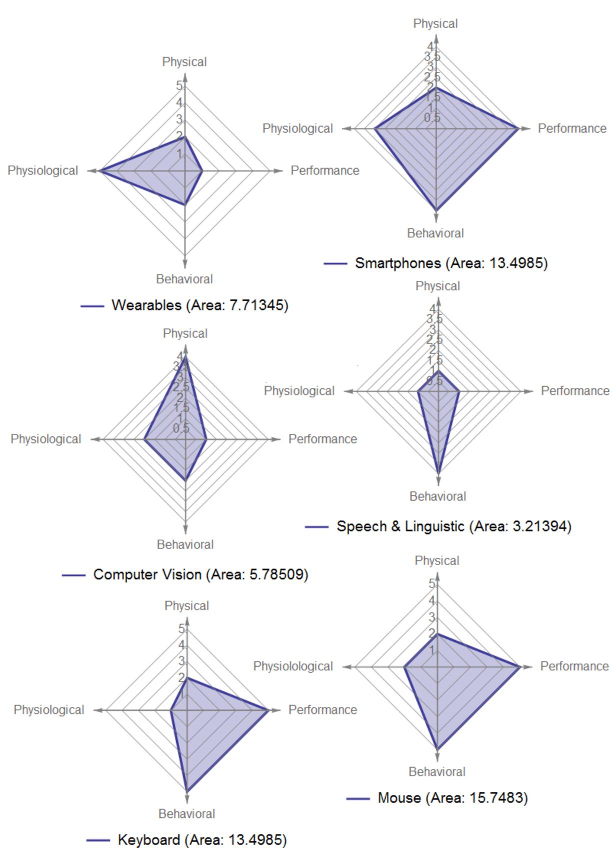

Fig. 12: Score of multimodality of each method.

from employees who did not agree to be monitored. Approaches based on speech are significantly less expensive. They do, however, suffer a similar problem in the sense that the speech of the employees must be acquired and processed. This is especially worrying when linguistic features based on the type of words used are employed. Moreover, microphone-based approaches are prone to errors in noisy environments.

Approaches based on wearable devices, which incorporate physiological sensors, are generally more accurate and allow the user to move freely around the environment. They do, however, require users to constantly wear one or more pieces of clothing or accessories. Moreover, they also tend to be expensive, especially if the aim is to monitor groups of people in an organization. This can constitute an obstacle to the implementation of initiatives for monitoring stress or well-being in the workplace.

When this is the aim, i.e., to monitor stress in modern workplaces, a special interest must be placed in the paradigm of Ambient Intelligence, in the sense that these technologically empowered environments can simultaneously be *sensitive* and *transparent*. That is, in AmI systems the user is constantly being monitored in a way that is completely non-intrusive and transparent. Ultimately, the user forgets about the monitoring and notices only the environment's contextualized actions.

This new view on the problem can be made possible through behavioral analysis. Under this approach, everything the user does (e.g. interactions with devices, movement patterns, interactions with other users) can be used as a potential input. Moreover, one can consider not only what the user does but *how* the user does it.

In fact, our behaviors are commonly associated with our inner states. We look at someone who is restless, biting the nails or fiddling and we instantly know that the person is nervous or stressed. We look at someone who is moving slowly, whose eyes are half closed and who gets distracted easily and we know that the person is tired. The fact is that, in an interaction, our behaviors often give away more information than the words we use. And we, as humans, have evolved to collect this information to, even in an unconscious way, better understand the state of the other individual. This information is actually paramount for the efficiency of the communication process.

The challenge thus lies in developing ways to acquire this information and use it as a way to perceive the user's inner state. Indeed, many of our behaviors can be used as input to classify our state. Namely, the way we type, the way we move the mouse, the way we hold or touch our smartphone, the way we talk or even the way we sit. While one of these features may not be enough to accurately describe the user's state, their combined use may constitute a reliable source of information.

The main advantage of this approach is, undoubtedly, that it can be used continuously throughout the day, without interfering with the users' routines. It is transparent, non-intrusive and pervasive. It allows for behavioral models to be trained in short time-frames that allow us to know one's frequent behaviors when in neutral states as well as in specific states. These models can be dependent on many variables (that can also be acquired by the environment) including geographical, social or historic context.

Given this, the most suited approaches to assess stress in the workplace are, in our opinion, the behavioral ones [95]. This is especially so in workplaces in which employees interact with a computer for long periods, such as the so-called white-collar jobs. In these scenarios, approaches based on keyboard and mouse dynamics are especially suited. Specifically: (1) they are not intrusive as they are based on the interaction of the individual with the computer; (2) they are not expensive as they are based on the mouse and the keyboard; (3) they safeguard privacy as it is not necessary to determine what the employees are doing, only how they are doing it; (4) they allow the training and development of fairly simple models, based on features that are easily acquired and processed; (5) they can be used continuously throughout the day, providing real-time feedback about the state of the individual; and (6) they can provide information about other important aspects, namely the level of mental fatigue [96].

One key conclusion of this survey is thus that if we consider modern workplaces, the best suited approach for continuously assessing stress is a behavioral one, based on the analysis of the interaction patterns of the workers with the computer. Moreover, stress management tecniques should be considered as stress may have positive effects even in the workplace [97], especially for small periods of time.

Nonetheless, such approaches should always take into consideration individual characteristics (i.e. some people are naturally more stressed than others) and contextual factors (e.g. in some scenarios, such as brainstorming, an increased level of stress is more acceptable than in others). This can only be achieved through the development of individualized models, that shape each individual's characteristics.

In order for this field to continue to develop towards high reliability and acceptance, we believe that future efforts should be guided by the following main lines:

- Personalized models should be trained to shape each individual's reaction to stress, also considering other important aspects such as workload, context, task difficulty, etc.;
- A framework for stress must be defined that identifies and incorporates the key stressors in the workplace and their effect on the level of stress;
- Stress management/reduction techniques must take into consideration the fact that not all individuals and situations are alike.

In terms of the "goodness" of each method, it is impossible to point out, in absolute terms, the best method. In a general way, the methods that achieve the highest score are those based on the mouse and the keyboard. These methods also achieve high scores in characteristics such as cost-effectiveness, low intrusiveness or privacy. However, if the focus of the organization is on accuracy, methods such as computer vision or wearables should be considered instead (or in addition). These methods are, however, also those that represent the higher cost.

The best method or group of methods for assessing stress in a given environment will always depend on the characteristics of the environment (e.g. are there video cameras available?, Do the individuals interact with the mouse and the keyboard?), on the constraints (e.g. is the cost of the method a limitation?, Is it possible to record speech?) and on the weight of each characteristic for the organization (e.g. privacy, accuracy, versatility).

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References

[1] T. A. Beehr and R. S. Bhagat, *Human stress and cognition in organizations: An integrated perspective*. Wiley-Interscience, 1985.

[2] T. A. Beehr, *Psychological Stress in the Workplace (Psychology Revivals)*. Routledge, 2014.

[3] D. Carneiro, P. Novais, R. Costa, P. Gomes, and J. Neves, "Emon: embodied monitorization," in *European Conference on Ambient Intelligence*. Springer, 2009, pp. 133–142.

[4] S. Jones, S. Hara, and J. C. Augusto, "efriend: an ethical framework for intelligent environments development," *Ethics and Information Technology*, vol. 17, no. 1, pp. 11–25, 2015.

[5] D. Carneiro, A. Pimenta, S. Gonçalves, J. Neves, and P. Novais, "Monitoring and improving performance in human–computer interaction," *Concurrency and Computation: Practice and Experience*, 2015.

[6] M. Weiser, "The computer for the 21st century," *SIGMOBILE Mob. Comput. Commun. Rev.*, vol. 3, no. 3, pp. 3–11, Jul. 1999. [Online]. Available: http://doi.acm.org/10.1145/329124.329126

[7] E. Aarts, R. Harwig, and S. M, *Ambient Intelligence*. McGraw-Hill, Inc., 2001.

[8] J. C. Augusto, V. Callaghan, D. Cook, A. Kameas, and I. Satoh, "Intelligent environments: a manifesto," *Human-Centric Computing and Information Sciences*, vol. 3, no. 1, pp. 1–18, 2013.

[9] J. C. Augusto, "Ambient intelligence: Basic concepts and applications," in *Software and Data Technologies*. Springer, 2006, pp. 16–26.

[10] G. van den Broek, F. Cavallo, and C. Wehrmann, *AALIANCE ambient assisted living roadmap*. IOS press, 2010, vol. 6.

[11] J. M. Fernandez, J. C. Augusto, R. Seepold, and N. M. Madrid, "A sensor technology survey for a stress-aware trading process," *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, vol. 42, no. 6, pp. 809–824, 2012.

[12] G. P. Chrousos and P. W. Gold, "The concepts of stress and stress system disorders: overview of physical and behavioral homeostasis," *Jama*, vol. 267, no. 9, pp. 1244–1252, 1992.

[13] I. Donald, P. Taylor, S. Johnson, C. Cooper, S. Cartwright, and S. Robertson, "Work environments, stress, and productivity: An examination using asset." *International Journal of Stress Management*, vol. 12, no. 4, p. 409, 2005.

[14] J. M. Weiss, "Somatic effects of predictable and unpredictable shock." *Psychosomatic Medicine*, vol. 32, no. 4, pp. 397–408, 1970.

[15] H. Selye, "The stress of life. edição revista," 1978.

[16] J. E. Dimsdale and J. Moss, "Plasma catecholamines in stress and exercise," *Jama*, vol. 243, no. 4, pp. 340–342, 1980.

[17] W. Liao, W. Zhang, Z. Zhu, Q. Ji, and W. D. Gray, "Toward a decision-theoretic framework for affect recognition and user assistance," *International Journal of Human-Computer Studies*, vol. 64, no. 9, pp. 847–873, 2006.

[18] A. Soylu, S. Kavukçu, M. Türkmen, N. Çabuk, and M. Duman, "Effect of socioeconomic status on the blood pressure in children living in a developing country," *Pediatrics International*, vol. 42, no. 1, pp. 37–42, 2000.

[19] G. W. Evans, M. Bullinger, and S. Hygge, "Chronic noise exposure and physiological response: A prospective study of children living under environmental stress," *Psychological science*, vol. 9, no. 1, pp. 75–77, 1998.

[20] S. E. Stockdale, K. B. Wells, L. Tang, T. R. Belin, L. Zhang, and C. D. Sherbourne, "The importance of social context: neighborhood stressors, stress-buffering mechanisms, and alcohol, drug, and mental health disorders," *Social science & medicine*, vol. 65, no. 9, pp. 1867–1881, 2007.

[21] I. H. Meyer, "Prejudice, social stress, and mental health in lesbian, gay, and bisexual populations: conceptual issues and research evidence." *Psychological bulletin*, vol. 129, no. 5, p. 674, 2003.

[22] G. H. Elder and A. Caspi, "Economic stress in lives: Developmental perspectives," *Journal of Social Issues*, vol. 44, no. 4, pp. 25–45, 1988.

[23] J. O. Berry and W. H. Jones, "The parental stress scale: Initial psychometric evidence," *Journal of Social and Personal Relationships*, vol. 12, no. 3, pp. 463–472, 1995.

[24] L. Fagin, "Stress and unemployment," *Stress medicine*, vol. 1, no. 1, pp. 27–36, 1985.

[25] S. T. Tidd and R. A. Friedman, "Conflict style and coping with role conflict: An extension of the uncertainty model of work stress," *International Journal of Conflict Management*, vol. 13, no. 3, pp. 236–257, 2002.

[26] M. Vollrath, "Personality and stress," *Scandinavian Journal of Psychology*, vol. 42, no. 4, pp. 335–347, 2001.

[27] T. W. Colligan and E. M. Higgins, "Workplace stress: Etiology and consequences," *Journal of workplace behavioral health*, vol. 21, no. 2, pp. 89–97, 2006.

[28] B. H. Gottlieb, *Coping with chronic stress*. Springer Science & Business Media, 2013.

[29] T. Theorell and R. A. Karasek, "Current issues relating to psychosocial job strain and cardiovascular disease research." *Journal of occupational health psychology*, vol. 1, no. 1, p. 9, 1996.

[30] J. V. Johnson and E. M. Hall, "Job strain, work place social support, and cardiovascular disease: a cross-sectional study of a random sample of the swedish working population." *American journal of public health*, vol. 78, no. 10, pp. 1336–1342, 1988.

[31] N. Krause, "Social support, stress, and well-being among older adults," *Journal of gerontology*, vol. 41, no. 4, pp. 512–519, 1986.

[32] K. Daniels and A. Guppy, "Occupational stress, social support, job control, and psychological well-being," *Human Relations*, vol. 47, no. 12, pp. 1523–1544, 1994.

[33] A. B. Bakker and E. Demerouti, "The job demands-resources model: State of the art," *Journal of managerial psychology*, vol. 22, no. 3, pp. 309–328, 2007.

[34] J. R. Aiello and K. J. Kolb, "Electronic performance monitoring and social context: impact on productivity and stress." *Journal of Applied Psychology*, vol. 80, no. 3, p. 339, 1995.

[35] L. Gallatin, *Electronic Monitoring in the Workplace: Supervision Or Surveillance?* CNOT (241 St. Botolph St., Boston, MA 02115), 1989.

[36] R. Irving, C. A. Higgins, and F. R. Safayeni, "Computerized performance monitoring systems: Use and abuse," *Communications of the ACM*, vol. 29, no. 8, pp. 794–801, 1986.

[37] M. J. Smith, P. Carayon, K. J. Sanders, S.-Y. Lim, and D. LeGrande, "Employee stress and health complaints in jobs with and without electronic performance monitoring," *Applied Ergonomics*, vol. 23, no. 1, pp. 17–27, 1992.

[38] B. C. Amick and M. J. Smith, "Stress, computer-based work monitoring and measurement systems: A conceptual overview," *Applied Ergonomics*, vol. 23, no. 1, pp. 6–16, 1992.

[39] R. C. Kessler, C. Barber, H. G. Birnbaum, R. G. Frank, P. E. Greenberg, R. M. Rose, G. E. Simon, and P. Wang, "Depression in the workplace: effects on short-term disability," *Health affairs*, vol. 18, no. 5, pp. 163–171, 1999.

[40] P. E. Greenberg, L. E. Stiglin, S. N. Finkelstein, and E. R. Berndt, "The economic burden of depression in 1990." *Journal of Clinical Psychiatry*, 1993.

[41] B. Yang, D. Lester, and S. WACHTER, "Subjective stress and productivity in real estate sales people: a replication," *Psychological reports*, vol. 67, no. 3, pp. 738–738, 1990.

[42] M. Jamal and V. Baba, "Stressful jobs and employee productivity: Results from studies on managers, blue-collar workers and nurses," *International Journal of Management*, vol. 9, no. 1, pp. 62–67, 1992.

[43] D. L. Jones, T. Tanigawa, and S. M. Weiss, "Stress management and workplace disability in the us, europe and japan." *Journal of occupational health*, vol. 45, no. 1, pp. 1–7, 2003.

[44] C. I. of Personnel and Development. (2008) Building the business case for managing stress in the workplace. [Online]. Available: https://www.cipd.co.uk/hr-resources/guides/building-business-case-managing-stress-workplace.aspx

[45] K. P. Eisen, G. J. Allen, M. Bollash, and L. S. Pescatello, "Stress management in the workplace: A comparison of a computer-based and an in-person stress-management intervention," *Computers in Human Behavior*, vol. 24, no. 2, pp. 486–496, 2008.

[46] S. Ackroyd, *Data collection in context*. Longman Group United Kingdom, 1992.

[47] K. Popper, *The logic of scientific discovery*. Routledge, 2005.

[48] J. Milne, "Questionnaires: advantages and disadvantages," *Evaluation cookbook*, 1999.

[49] S. Levenstein, C. Prantera, V. Varvo, M. L. Scribano, E. Berto, C. Luzi, and A. Andreoli, "Development of the perceived stress questionnaire: a new tool for psychosomatic research," *Journal of psychosomatic research*, vol. 37, no. 1, pp. 19–32, 1993.

[50] T. Haratani, N. Kawakami, and S. Araki, "Reliability and validity of the japanese version of niosh generic job stress questionnaire," *Jpn J Ind Health*, vol. 35, p. S214, 1993.

[51] M. Nübling, U. Stößel, H.-M. Hasselhorn, M. Michaelis, and F. Hofmann, "Measuring psychological stress and strain at work-evaluation of the copsoq questionnaire in germany," *GMS Psycho-Social Medicine*, vol. 3, 2006.

[52] S. M. Staufenbiel, B. W. Penninx, A. T. Spijker, B. M. Elzinga, and E. F. van Rossum, "Hair cortisol, stress exposure, and mental health in humans: a systematic review," *Psychoneuroendocrinology*, vol. 38, no. 8, pp. 1220–1235, 2013.

[53] C. Kirschbaum and D. H. Hellhammer, "Salivary cortisol in psychoneuroendocrine research: recent developments and applications," *Psychoneuroendocrinology*, vol. 19, no. 4, pp. 313–333, 1994.

[54] D. H. Hellhammer, S. Wüst, and B. M. Kudielka, "Salivary cortisol as a biomarker in stress research," *Psychoneuroendocrinology*, vol. 34, no. 2, pp. 163–171, 2009.

[55] A. Barreto, J. Zhai, and M. Adjouadi, "Non-intrusive physiological monitoring for automated stress detection in human-computer interaction," in *Human–Computer Interaction*. Springer, 2007, pp. 29–38.

[56] J. Healey, R. W. Picard *et al.*, "Detecting stress during real-world driving tasks using physiological sensors," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 6, no. 2, pp. 156–166, 2005.

[57] C. Brüser, K. Stadlthanner, S. De Waele, and S. Leonhardt, "Adaptive beat-to-beat heart rate estimation in ballistocardiograms," *Information Technology in Biomedicine, IEEE Transactions on*, vol. 15, no. 5, pp. 778–786, 2011.

[58] L. Bernardi, J. Wdowczyk-Szulc, C. Valenti, S. Castoldi, C. Passino, G. Spadacini, and P. Sleight, "Effects of controlled breathing, mental activity and mental stress with or without verbalization on heart rate variability," *Journal of the American College of Cardiology*, vol. 35, no. 6, pp. 1462–1469, 2000.

[59] M. S. Schwartz and F. E. Andrasik, *Biofeedback: A practitioner's guide* . Guilford Press, 2003.

[60] J. F. Lubar, "Discourse on the development of eeg diagnostics and biofeedback for attention-deficit/hyperactivity disorders," *Biofeedback and Self-regulation*, vol. 16, no. 3, pp. 201–225, 1991.

[61] A. de Santos Sierra, C. S. Ávila, J. G. Casanova, and G. B. D. Pozo, "A stress-detection system based on physiological signals and fuzzy logic," *Industrial Electronics, IEEE Transactions on*, vol. 58, no. 10, pp. 4857–4865, 2011.

[62] F.-T. Sun, C. Kuo, H.-T. Cheng, S. Buthpitiya, P. Collins, and M. Griss, "Activity-aware mental stress detection using physiological sensors," in *Mobile computing, applications, and services*. Springer, 2010, pp. 211–230.

[63] J. Zhai and A. Barreto, "Stress detection in computer users through non-invasive monitoring of physiological signals," *Blood*, vol. 5, p. 0, 2008.

[64] M. Jiang and Z. Wang, "A method for stress detection based on fcm algorithm," in *Image and Signal Processing, 2009. CISP'09. 2nd International Congress on*. IEEE, 2009, pp. 1–5.

[65] J. Bakker, M. Pechenizkiy, and N. Sidorova, "What's your current stress level? detection of stress patterns from gsr sensor data," in *Data Mining Workshops (ICDMW), 2011 IEEE 11th International Conference on*. IEEE, 2011, pp. 573–580.

[66] P. Melillo, M. Bracale, L. Pecchia *et al.*, "Nonlinear heart rate variability features for real-life stress detection. case study: students under stress due to university examination," *Biomed Eng Online*, vol. 10, no. 1, p. 96, 2011.

[67] M. Chan, D. Estève, J.-Y. Fourniols, C. Escriba, and E. Campo, "Smart wearable systems: Current status and future challenges," *Artificial intelligence in medicine*, vol. 56, no. 3, pp. 137–156, 2012.

[68] J. Choi, B. Ahmed, and R. Gutierrez-Osuna, "Development and evaluation of an ambulatory stress monitor based on wearable sensors," *Information Technology in Biomedicine, IEEE Transactions on*, vol. 16, no. 2, pp. 279–286, 2012.

[69] C. Setz, B. Arnrich, J. Schumm, R. La Marca, G. Troster, and U. Ehlert, "Discriminating stress from cognitive load using a wearable eda device," *Information Technology in Biomedicine, IEEE Transactions on*, vol. 14, no. 2, pp. 410–417, 2010.

[70] E. Ertin, N. Stohs, S. Kumar, A. Raij, M. al'Absi, and S. Shah, "Autosense: unobtrusively wearable sensor suite for inferring the onset, causality, and consequences of stress in the field," in *Proceedings of the 9th ACM Conference on Embedded Networked Sensor Systems*. ACM, 2011, pp. 274–287.

[71] P. Sanches, K. Höök, E. Vaara, C. Weymann, M. Bylund, P. Ferreira, N. Peira, and M. Sjölinder, "Mind the body!: designing a mobile stress management application encouraging personal reflection," in *Proceedings of the 8th ACM conference on designing interactive systems*. ACM, 2010, pp. 47–56.

[72] A. Kailas, C.-C. Chong, and F. Watanabe, "From mobile phones to personal wellness dashboards," *Pulse, IEEE*, vol. 1, no. 1, pp. 57–63, 2010.

[73] M. F. Colunas, J. M. A. Fernandes, I. C. Oliveira, and J. P. S. Cunha, "Droid jacket: Using an android based smartphone for team monitoring," in *Wireless Communications and Mobile Computing Conference (IWCMC), 2011 7th International*. IEEE, 2011, pp. 2157–2161.

[74] A. Gaggioli, G. Pioggia, G. Tartarisco, G. Baldus, M. Ferro, P. Cipresso, S. Serino, A. Popleteev, S. Gabrielli, R. Maimone *et al.*, "A system for automatic detection of momentary stress in naturalistic settings," *Stud Health Technol Inform*, vol. 181, pp. 182–186, 2012.

[75] H. Lu, D. Frauendorfer, M. Rabbi, M. S. Mast, G. T. Chittaranjan, A. T. Campbell, D. Gatica-Perez, and T. Choudhury, "Stresssense: Detecting stress in unconstrained acoustic environments using smartphones," in *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*. ACM, 2012, pp. 351–360.

[76] G. Bauer and P. Lukowicz, "Can smartphones detect stress-related changes in the behaviour of individuals?" in *Pervasive Computing and Communications Workshops (PERCOM Workshops), 2012 IEEE International Conference on*. IEEE, 2012, pp. 423–426.

[77] D. F. Dinges, R. L. Rider, J. Dorrian, E. L. McGlinchey, N. L. Rogers, Z. Cizman, S. K. Goldenstein, C. Vogler, S. Venkataraman, and D. N. Metaxas, "Optical computer recognition of facial expressions associated with stress induced by performance demands," *Aviation, space, and environmental medicine*, vol. 76, no. Supplement 1, pp. B172–B182, 2005.

[78] H. Gao, A. Yuce, and J.-P. Thiran, "Detecting emotional stress from facial expressions for driving safety," in *Image Processing (ICIP), 2014 IEEE International Conference on*. IEEE, 2014, pp. 5961–5965.

[79] W. Liao, W. Zhang, Z. Zhu, and Q. Ji, "A real-time human stress monitoring system using dynamic bayesian network," in *Computer Vision and Pattern Recognition-Workshops, 2005. CVPR Workshops. IEEE Computer Society Conference on*. IEEE, 2005, pp. 70–70.

[80] A. Derakhshan, M. Mikaeili, M. A. Khalilzadeh, and A. Mohammadian, "Preliminary study on facial thermal imaging for stress recognition." in *Intelligent Environments (Workshops)*, 2014, pp. 66–73.

[81] D. Giakoumis, A. Drosou, P. Cipresso, D. Tzovaras, G. Hassapis, A. Gaggioli, and G. Riva, "Using activity-related behavioural features towards more effective automatic stress detection," *PloS one*, vol. 7, no. 9, p. e43571, 2012.

[82] N. Sharma, A. Dhall, T. Gedeon, and R. Goecke, "Thermal spatio-temporal data for stress recognition," *EURASIP Journal on Image and Video Processing*, vol. 2014, no. 1, pp. 1–12, 2014.

[83] L. M. Vizer, L. Zhou, and A. Sears, "Automated stress detection using keystroke and linguistic features: An exploratory study," *International Journal of Human-Computer Studies*, vol. 67, no. 10, pp. 870–886, 2009.

[84] G. Zhou, J. H. Hansen, and J. F. Kaiser, "Nonlinear feature based classification of speech under stress," *Speech and Audio Processing, IEEE Transactions on*, vol. 9, no. 3, pp. 201–216, 2001.

[85] M. Lai, Y. Chen, M. Chu, Y. Zhao, and F. Hu, "A hierarchical approach to automatic stress detection in english sentences," in *Acoustics, Speech and Signal Processing, 2006. ICASSP 2006 Proceedings. 2006 IEEE International Conference on*, vol. 1. IEEE, 2006, pp. I–I.

[86] K. Imoto, Y. Tsubota, T. Kawahara, and M. Dantsuji, "Modeling and automatic detection of english sentence stress for computer-assisted english prosody learning system," *Acoustical science and technology*, vol. 24, no. 3, pp. 159–160, 2003.

[87] H. Xie, M. Zhang, and P. Andreae, "Genetic programming for automatic stress detection in spoken english," in *Applications of Evolutionary Computing*. Springer, 2006, pp. 460–471.

[88] J. Zhao, H. Yuan, J. Liu, and S. Xia, "Automatic lexical stress detection using acoustic features for computer assisted language learning," *Proc. APSIPA ASC*, pp. 247–251, 2011.

[89] J. Hernandez, P. Paredes, A. Roseway, and M. Czerwinski, "Under pressure: sensing stress of computer users," in *Proceedings of the SIGCHI conference on Human factors in computing systems*. ACM, 2014, pp. 51–60.

[90] D. Sun, P. Paredes, and J. Canny, "Moustress: detecting stress from mouse motion," in *Proceedings of the SIGCHI conference on Human factors in computing systems*. ACM, 2014, pp. 61–70.

[91] Y. M. Lim, A. Ayesh, and M. Stacey, "Detecting cognitive stress from keyboard and mouse dynamics during mental arithmetic," in *Science and Information Conference (SAI), 2014*. IEEE, 2014, pp. 146–152.

[92] D. Carneiro, P. Novais, J. M. Pêgo, N. Sousa, and J. Neves, "Using mouse dynamics to assess stress during online exams," in *Hybrid Artificial Intelligent Systems*. Springer, 2015, pp. 345–356.

[93] M. Rodrigues, S. Gonçalves, D. Carneiro, P. Novais, and F. Fdez-Riverola, "Keystrokes and clicks: Measuring stress on e-learning students," in *Management Intelligent Systems*. Springer, 2013, pp. 119–126.

[94] J. Andrén and P. Funk, "A case-based approach using behavioural biometrics to determine a user's stress level." in *ICCBR Workshops*, 2005, pp. 9–17.

[95] D. Carneiro, J. C. Castillo, P. Novais, A. Fernández-Caballero, and J. Neves, "Multimodal behavioral analysis for non-invasive stress detection," *Expert Systems with Applications*, vol. 39, no. 18, pp. 13 376–13 389, 2012.

[96] A. Pimenta, D. Carneiro, P. Novais, and J. Neves, "Monitoring mental fatigue through the analysis of keyboard and mouse interaction patterns," in *Hybrid Artificial Intelligent Systems*. Springer, 2013, pp. 222–231.

[97] M. B. Hargrove, D. L. Nelson, and C. L. Cooper, "Generating eustress by challenging employees," *Organizational Dynamics*, vol. 42, no. 1, pp. 61–69, 2013.

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